MovieLens Report

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###Introduction

A recommender system or a recommendation system is a subclass of information filtering system that seeks to predict the "rating" or "preference" a user would give to an item. Recommendation systems use ratings that users have given items to make specific recommendations. Companies that sell many products to many customers and permit these customers to rate their products, use customers rating to predict their preferences or rating for another item. Netflix uses a recommendation system to predict if user rating for specific movies. motivated by some of the approaches taken by the winners of the Netflix challenges, On October 2006, Netflix offered a challenge to the data science community: improve our recommendation algorithm by 10% and win a million dollars. In September 2009, the winners were announced. You can read a good summary of how the winning algorithm was put together here and a more detailed explanation here. We will now show you some of the data analysis strategies used by the winning team.

this assignment is to accomplish a similar goal which is to build a recommendation system that recommends movies based on a rating scale.

##Data set for this project the MovieLens Data set collected by GroupLens Research and can be found in MovieLens web site (http://movielens.org).

##Data Loading the data set is loaded using the code provided by course instucture in this link https://bit.ly/2Ng6tVW which split the data into edx set and 10% validation set. the edx set will be split into training and test set,and validation set will be used to final evaluation.

```r
#############################################################
# Create edx set, validation set, and submission file
#############################################################

# Note: this process could take a couple of minutes

if(!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")
if(!require(caret)) install.packages("caret", repos = "http://cran.us.r-project.org")

# MovieLens 10M dataset:
# https://grouplens.org/datasets/movielens/10m/
# http://files.grouplens.org/datasets/movielens/ml-10m.zip

dl <- tempfile()
download.file("http://files.grouplens.org/datasets/movielens/ml-10m.zip", dl)

ratings <- read.table(text = gsub("::", "\t", readLines(unzip(dl, "ml-10M100K/ratings.dat"))),
                      col.names = c("userId", "movieId", "rating", "timestamp"))

movies <- str_split_fixed(readLines(unzip(dl, "ml-10M100K/movies.dat")), "\\::", 3)
colnames(movies) <- c("movieId", "title", "genres")
```

```r
movies <- as.data.frame(movies) %>% mutate(movieId = as.numeric(levels(movieId))[movieId],
                                           title = as.character(title),
                                           genres = as.character(genres))

movielens <- left_join(ratings, movies, by = "movieId")

# Validation set will be 10% of MovieLens data

set.seed(1)
test_index <- createDataPartition(y = movielens$rating, times = 1, p = 0.1, list = FALSE)
edx <- movielens[-test_index,]
temp <- movielens[test_index,]

# Make sure userId and movieId in validation set are also in edx set
#validation set

validation <- temp %>%
  semi_join(edx, by = "movieId") %>%
  semi_join(edx, by = "userId")

# Add rows removed from validation set back into edx set

removed <- anti_join(temp, validation)
```

```
## Joining with `by = join_by(userId, movieId, rating, timestamp, title,
## genres)`
```

```r
edx <- rbind(edx, removed)

rm(dl, ratings, movies, test_index, temp, movielens, removed)

##################################################################################
##################################################
```

before the analysis we check for any NA value

```r
anyNA(edx)
```

```
## [1] TRUE
```

Data Summary and Explortory Data Analysis

after loading the data set we start by looking at the data structure and type we can see that there is six variable (userId,movieID,rating,timestamp,title,genres).as shown the year need to be seperated from title if needed for prediction also the genres need sepration if needed.

```r
str(edx)
```

```
## 'data.frame':    9000061 obs. of  6 variables:
##  $ userId   : int  1 1 1 1 1 1 1 1 1 1 ...
```

```
## $ movieId  : num  122 185 231 292 316 329 355 356 362 364 ...
## $ rating   : num  5 5 5 5 5 5 5 5 5 5 ...
## $ timestamp: int  838985046 838983525 838983392 838983421 838983392 838983392 838984474 838983653 8
## $ title    : chr  NA NA NA NA ...
## $ genres   : chr  NA NA NA NA ...
```

```r
summary(edx)
```

```
##      userId         movieId          rating        timestamp
## Min.   :    1   Min.   :    1   Min.   :0.500   Min.   :7.897e+08
## 1st Qu.:18122   1st Qu.:  648   1st Qu.:3.000   1st Qu.:9.468e+08
## Median :35743   Median : 1834   Median :4.000   Median :1.035e+09
## Mean   :35869   Mean   : 4120   Mean   :3.512   Mean   :1.033e+09
## 3rd Qu.:53602   3rd Qu.: 3624   3rd Qu.:4.000   3rd Qu.:1.127e+09
## Max.   :71567   Max.   :65133   Max.   :5.000   Max.   :1.231e+09
##    title              genres
## Length:9000061     Length:9000061
## Class :character   Class :character
## Mode  :character   Mode  :character
##
##
##
```

from the summary of data we see that the minimum rating is 1 and max is 5 and the mean for the rating is 3.512 and the mode is 4.0.

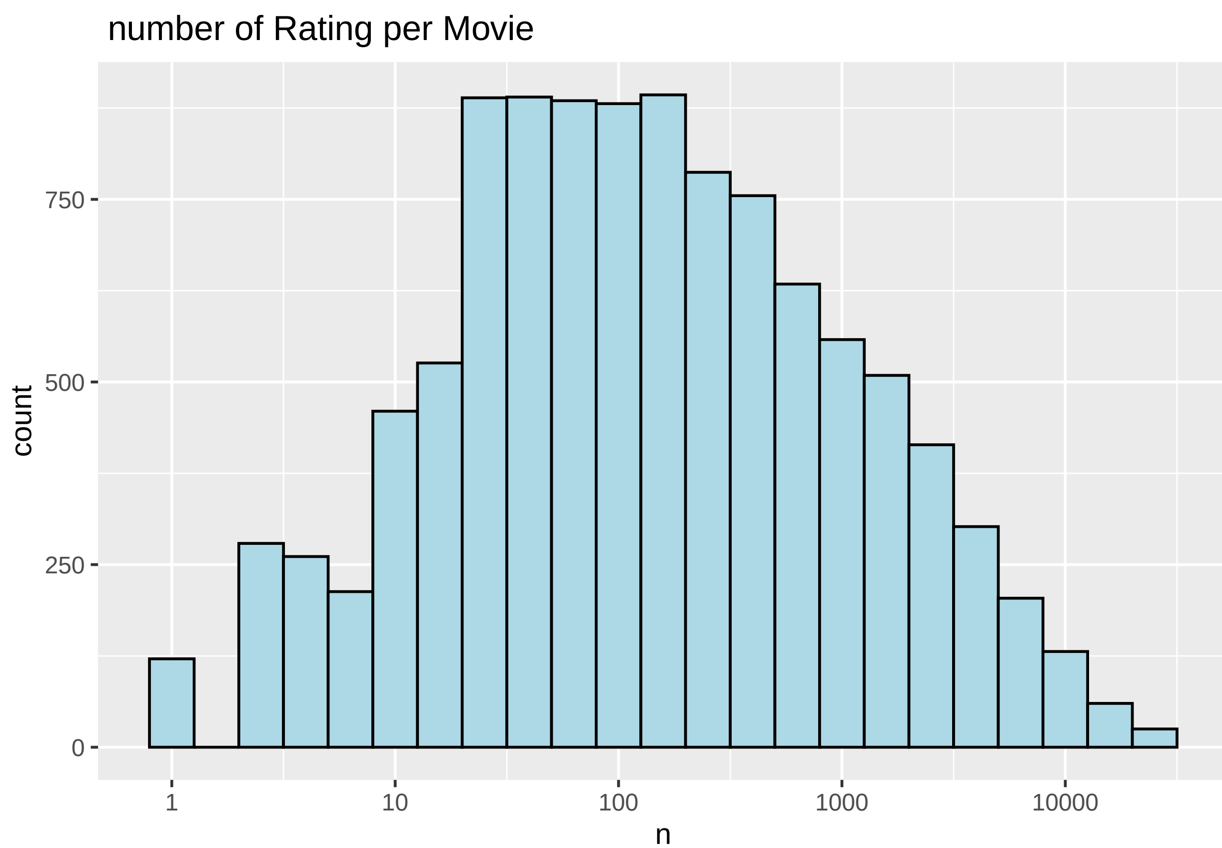
```
## Selecting by count

## # A tibble: 5 x 2
##   rating   count
##    <dbl>   <int>
## 1    4   2588021
## 2    3   2121638
## 3    5   1390541
## 4    3.5  792037
## 5    2    710998
```

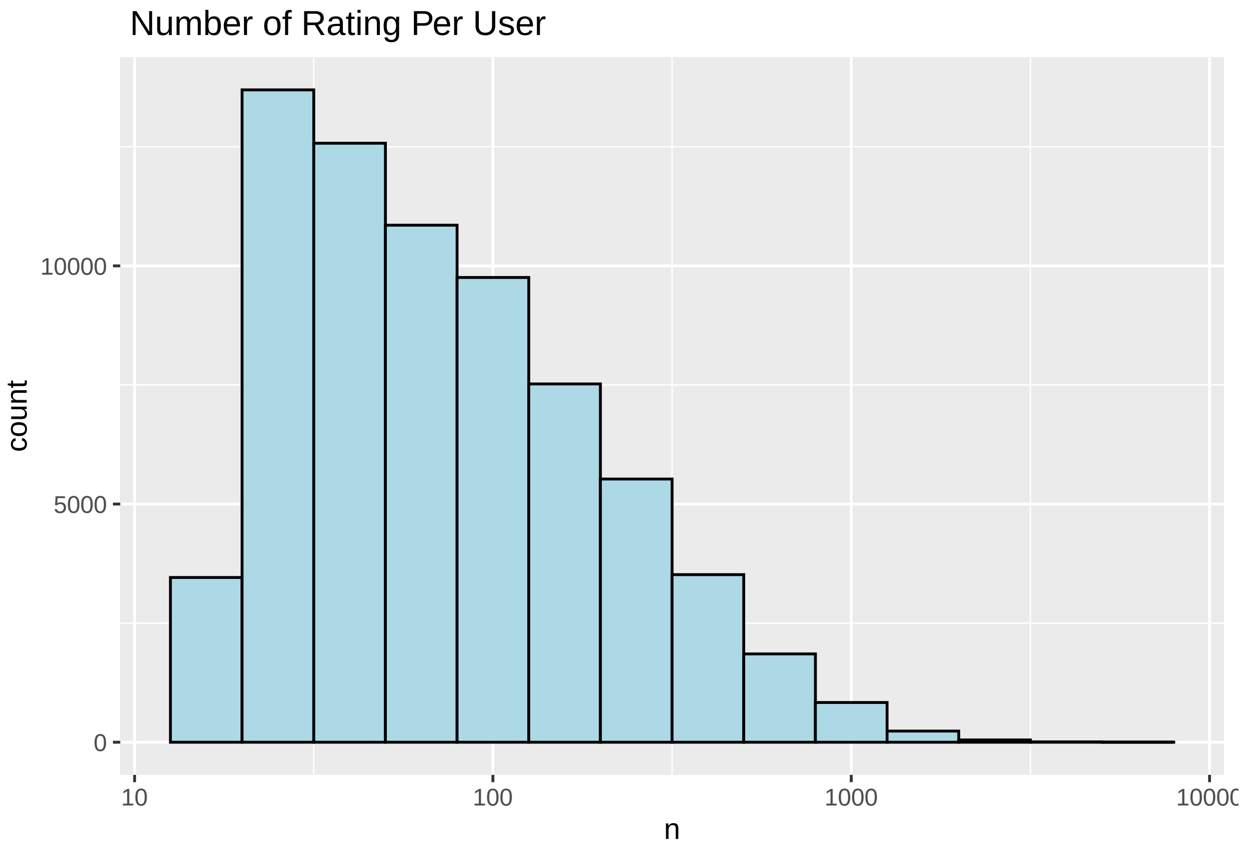
this code prints the number of unique movies and users in the data set:

```
##   n_users n_movies
## 1   69878    10677
```

to see how the number of ratings for every movie, we do that by plotting histogram

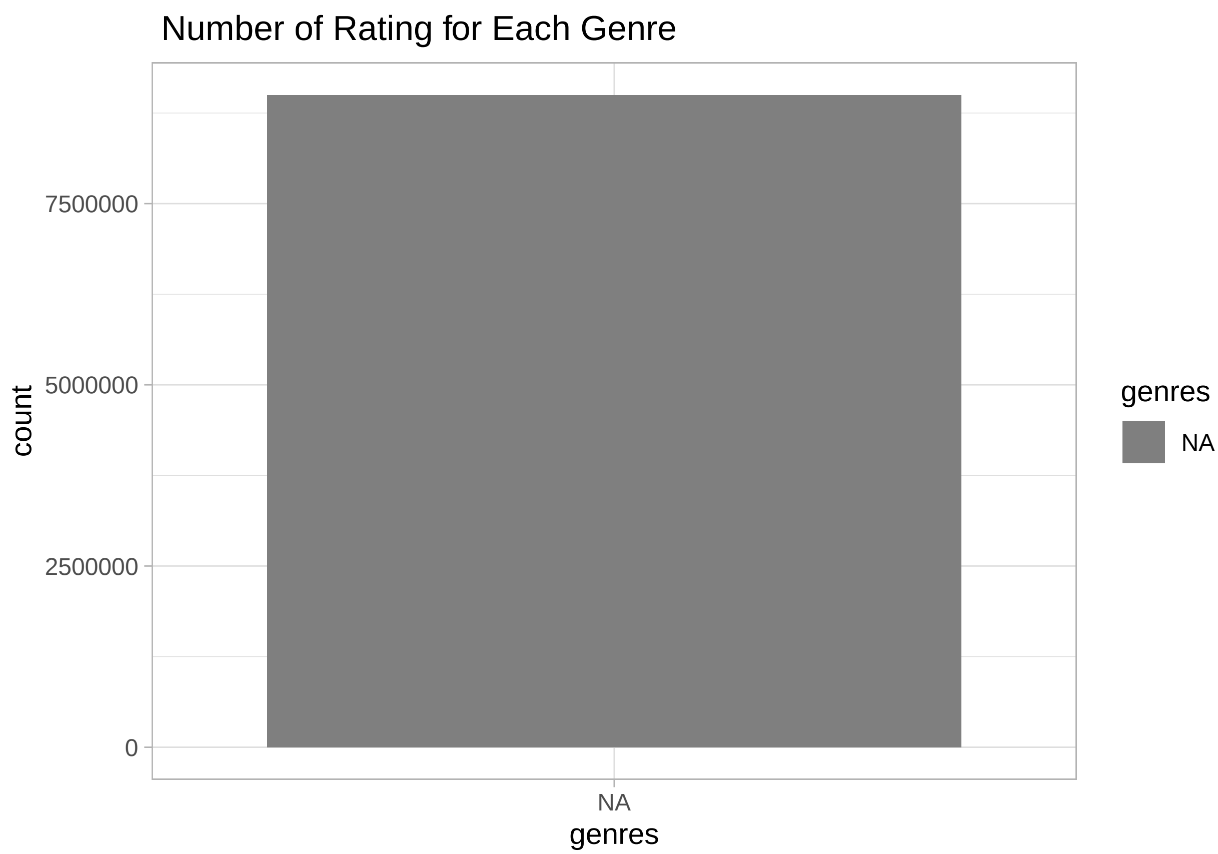


We note that some movies get more ratings it could be due to popularity. Now we visualize the number of ratings for each user



we see that some user are active more than others at rating movies.

Now let's plot the rating for each movie genre



let's see the top 10 most popular genre

```
## # A tibble: 1 x 2
##   genres   count
##   <chr>    <int>
## 1 <NA>   9000061
```

##Data Partitioning
before building the model we partition the edx data set into 20% for test set and 80% for the training set.

```
set.seed(1)
test_index <- createDataPartition(y = edx$rating, times = 1, p = 0.2, list = FALSE)
train_set <- edx[-test_index,]
test_set <- edx[test_index,]
```

Model building and RMSE calculation

The Netflix challenge used typical error loss. They decided on a winner based on the residual mean squared error (RMSE) on a test set. The RMSE will be the measure of accuracy.

```
RMSE <- function(true_ratings, predicted_ratings){
  sqrt(mean((true_ratings - predicted_ratings)^2, na.rm = TRUE))
}
```

###First Model In the first model, we predict the same rating for all movies regardless of the user. a model that assumes the same rating for all movies and users. no bias are considered here. this method assumes the following linear equation is true: $Y\ u,i\ =??+??\ u,i$

```
Mu_1 <- mean(train_set$rating)
Mu_1
```

```
## [1] 3.51238
```

```
naive_rmse <- RMSE(test_set$rating,Mu_1)
naive_rmse
```

```
## [1] 1.059648
```

this code creates a table for the RMSE result to store all the result from each method to compare.

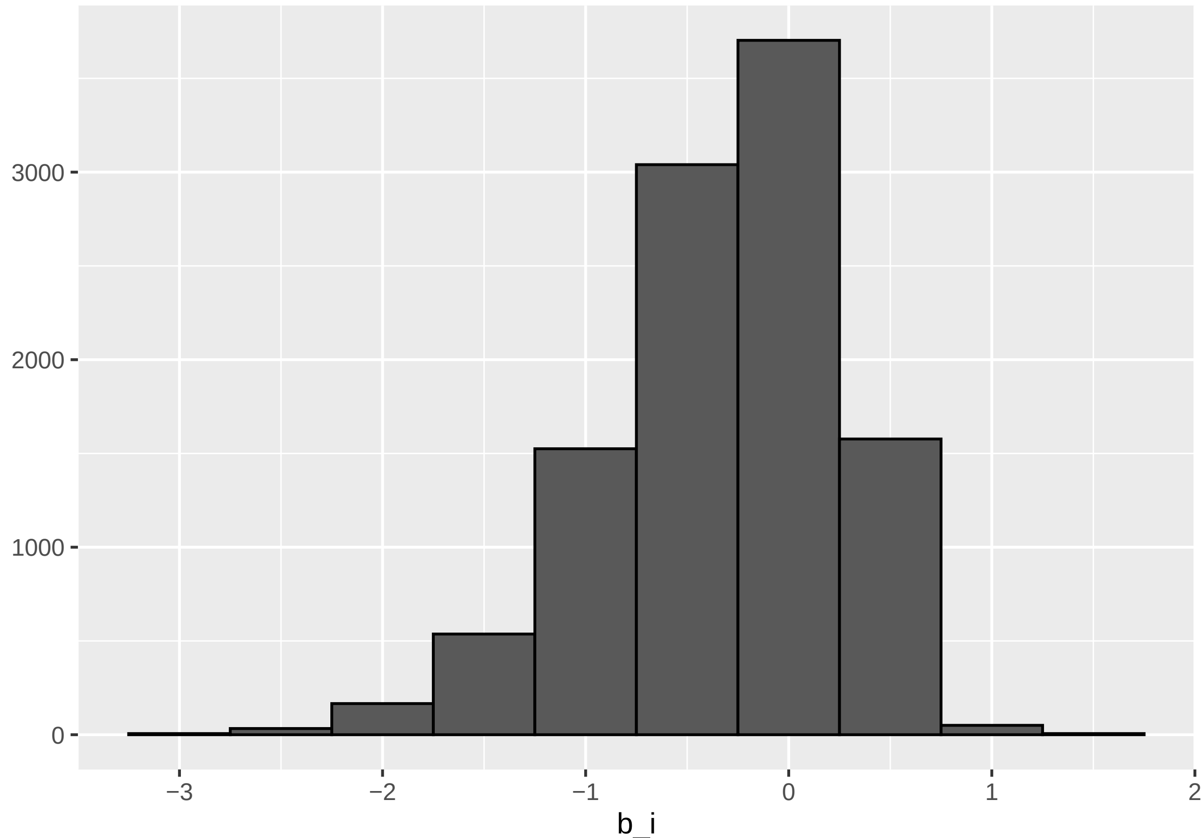
```
rmse_results <- data_frame(method = "Just the average", RMSE = naive_rmse)
rmse_results%>% knitr::kable()
```

method	RMSE
Just the average	1.059648

###Second Model| Movie Effect As we saw on the exploratory analysis some movies are rated more than other we can augment our previous model by adding the term $b\ i$ to represent the average ranking for movie i We can again use least squared to estimate considering the movie bias, in statics they refer to b as effect but in the Netflix paper referred them as "Bias" $Y\ u,i\ =?? + b\ i\ +??\ u,i$ Because there are thousands $b\ i$, each movie gets one, the lm() function will be very slow here. so we compute it using the average this way :

```
Mu_2 <- mean(train_set$rating)
movie_avgs <- train_set %>%
  group_by(movieId) %>%
  summarize(b_i = mean(rating - Mu_2))
```

we can see that variability in the estimate as plotted here



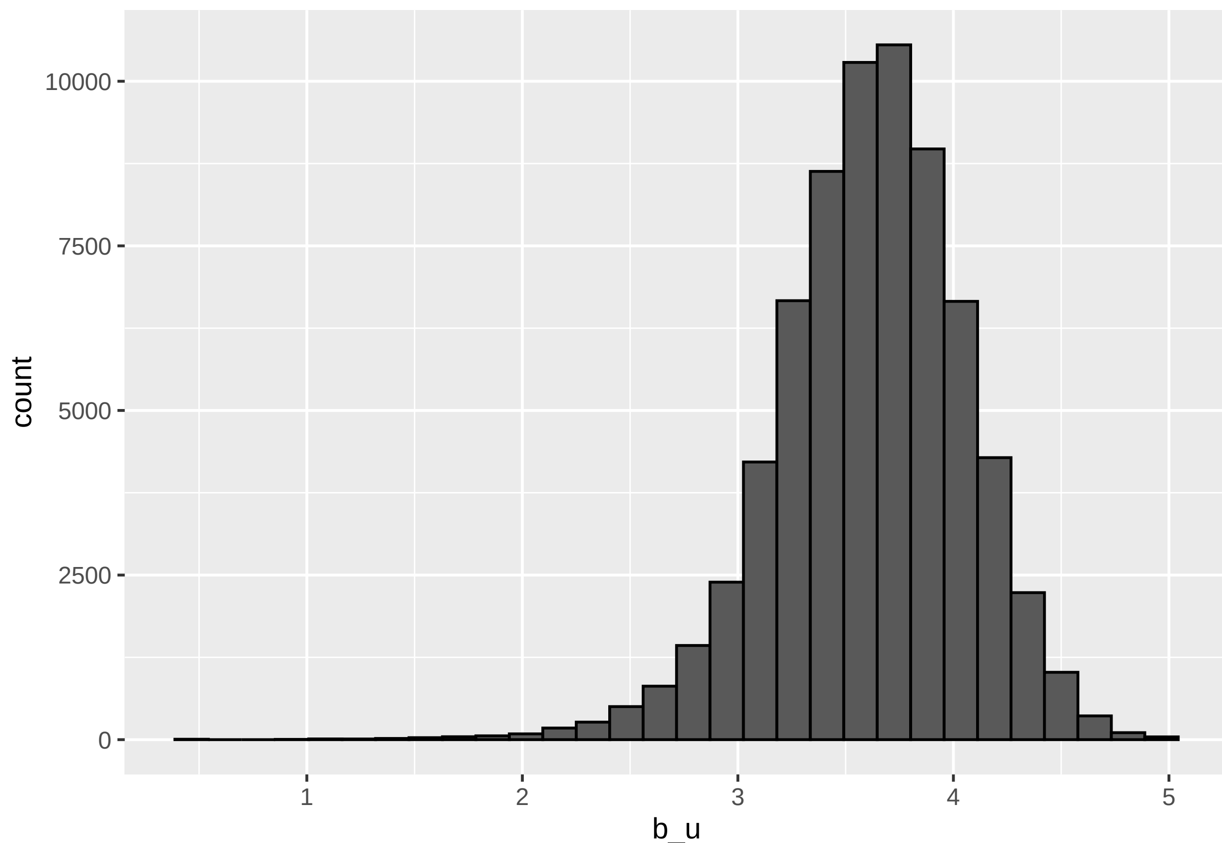
let's see how the prediction improves after altering the equation $Y \; u, i \; = ?? + b \; i$

```
predicted_ratings <- Mu_2 + test_set %>%
  left_join(movie_avgs, by='movieId') %>%
  pull(b_i)

model_2_rmse <- RMSE(predicted_ratings, test_set$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie Effect Model",
                                     RMSE = model_2_rmse))
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	1.0596481
Movie Effect Model	0.9431724

###Third Model| User Effect let's compure the user u for , for those who rated over 100 movies.



Notice that there is substantial variability across users ratings as well. This implies that a further improvement to our model may be $Y\ u,i\ =??+b\ i\ +??\ u,i$ we could fit this model by using use the lm() function but as mentioned earlier it would be very slow $lm(rating\ as.factor(movieId)+as.factor(userId))$ so here is the code

```
user_avgs <- train_set %>%
  left_join(movie_avgs, by='movieId') %>%
  group_by(userId) %>%
  summarize(b_u = mean(rating - Mu_2 - b_i))
```

now let's see how RMSE improved this time

```
predicted_ratings <- test_set %>%
  left_join(movie_avgs, by='movieId') %>%
  left_join(user_avgs, by='userId') %>%
  mutate(pred = Mu_2 + b_i + b_u) %>%
  pull(pred)


model_3_rmse <- RMSE(predicted_ratings, test_set$rating)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="Movie + User Effects Model",
                                     RMSE = model_3_rmse))
rmse_results%>% knitr::kable()
```

method	RMSE
Just the average	1.0596481
Movie Effect Model	0.9431724
Movie + User Effects Model	0.8655154

RMSE of the validation set

```
valid_pred_rating <- validation %>%
  left_join(movie_avgs , by = "movieId" ) %>%
  left_join(user_avgs , by = "userId") %>%
  mutate(pred = Mu_2 + b_i + b_u ) %>%
  pull(pred)

model_3_valid <- RMSE(validation$rating, valid_pred_rating)
rmse_results <-  bind_rows( rmse_results, data_frame(Method = "Validation Results" , RMSE = model_3_vali
rmse_results%>% knitr::kable()
```

method	RMSE	Method
Just the average	1.0596481	NA
Movie Effect Model	0.9431724	NA
Movie + User Effects Model	0.8655154	NA
NA	0.8666188	Validation Results

Conclusion

I have developed a naive approach, movie effect and user+movie effect the best RMSE given by the third model. for further analysis more complicated prediction using the release year of the movie as a bias considering old movies such as the 60 or 80 periods as another genre for a better predicting model. a linear model for precision is recommended.